Analysis of acoustic emission in cohesionless soil

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Analysis of Acoustic Emission in Cohesionless Soil

by

Jeyisanker Mathiyaparanam

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Civil Engineering Department of Civil and Environmental Engineering College of Engineering University of South Florida

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ACOUSTIC EMISSION IN COHESIONLESS SOIL

Jeyisanker Mathiyaparanam

ABSTRACT

Acoustic emission is a widely used nondestructive technique for identification of structural damage. The AE technique relies on transient energy waves generated by the materials during their failure. As for soils, the basic causes of acoustic emission are the mechanisms which are responsible for shearing of soils. Mobilization of shear strength within a soil itself and the interaction of the soil with the adjacent natural or construction materials are directly related to the level of acoustic emission in soils. It is envisioned that acoustic emission signals in deforming soils can be used as an early warning sign in real time landslide-monitoring systems.

This thesis study uses a laboratory experimental setup to record the acoustic emission signals emitted during the shearing of cohesionless soils. Several tests were performed with different rates of shearing with parallel (horizontal) and perpendicular (vertical) placement of the AE mote-sensor with respect to the shear plane. Since the original raw signals recorded contain large amounts of noise, it is necessary to de-noise them. The current study uses wavelet and FFT to de-noise the original signals. The filtered signals obtained using wavelet analysis and FFT are compared to determine the suitability of the two techniques. The peak AE values and the time taken to observe an initial visible peak under different conditions are reported in this study. It is observed that relatively faster rates of shearing generate more AE signals compared to slower rates of shearing. In addition, the rapid shearing produces initial visible peak AE activities within a short period of time than in slow rate of shearing.
CHAPTER 1
INTRODUCTION

1.1 Acoustic Emission

Acoustic Emission (AE) is one of the widely used nondestructive testing (NDT) techniques among the many emerging NDT techniques. The acoustic emission technique provides early indications of any small deformation that takes place during progressive failure. One of the advantages of AE compared to other NDT techniques is the possibility to observe damage processes during the entire loading history without any disturbance to the materials. AE related monitoring techniques rely on the detection of transient elastic waves emanating from stressed materials during their active flow. The induced stress can be tensile, compressive or shear. A certain strain is associated with any stress and hence under the stress, the material can expand, contract and/or shear. Depending on the stress level, the strain can be elastic strains or permanent (plastic) strains. A material under stress accumulates energy and a sudden deformation converts this energy to elastic waves, which generate acoustic emission signals. Acoustic emission is almost always associated with permanent strains.

Sources of acoustic emission can be classified as follows:

1. Dislocation movements
2. Phase transformation
3. Friction mechanisms
4. Crack formation and extension

Elastic waves are sound waves generated within a material. These elastic waves are called stress wave emissions, microseisms, micro seismic-activity, and acoustic emissions. By detecting and quantifying the AE from an active stressed material which
subsequently deforms, one can assess the stability of the material. Most of the AE waves are short-time transient events or burst signals of significant energy and propagate long distance in circles in all possible directions. Because of the above reason, AE testing must cover large, often inaccessible, monitored areas.

Often AE signals are not audible, because of their low amplitude or high frequency or both. However, by using an appropriate transducer, which converts mechanical energy into electrical energy, AE waves can be detected. There are various types of AE transducers. Among them, piezoelectric transducers are well-proven and by far the most widely used for AE testing. Piezoelectric transducers produce electrical signals proportional to the amplitude of the AE signals or vibration being detected. The sensor may be located some distance from the source and made to detect the signal subject to attenuation.

Typically, AE systems operate in the frequency range of 1 kHz to 2 MHz or greater. The lower frequency limit is imposed by background noises such as friction, outside impacts, or process generated signals that tend to mask acoustic emission. The upper frequency limit is imposed by attenuation, which tends to limit the range of detection of acoustic emission signals. A critical part of the AE application process is the selection of a suitable frequency range for AE detection and signal processing. It must be above the non-AE related background noises, while providing the necessary detection range (distance/frequency) and sensitivity to AE related signals. This is accomplished by the selection of AE sensors that operate in various narrow-band or wide-band frequency ranges and adoption of electronic signal filtering to remove unwanted noise.

When the acoustic emission source generates pulses, the detected signal is dependent on the characteristic of wave propagation between the sensor and the source and that of the sensor. Wave modes, velocity, attenuation, reflection, multiple path and reverberation are important factors in the propagation of AE waves. The wave velocity depends on material, wave modes (compression, shear, surface etc.) and thickness of the material in which the wave travels. When the wave travels, the peak amplitude drops due to attenuation. The most important causes of attenuation are listed below.
1. Geometric spreading of the waveform.
   - The amplitude decreases inversely, with distance in three-dimensional media or with the square root of distance in two-dimensional media.
   - Dominant close to the source.
2. Absorption or damping in the propagation medium.
   - The amplitude usually decreases exponentially with distance.
   - Dominant far from the source.
   - Material properties are dependent on the frequency (higher frequency AE signals undergo higher attenuation than lower frequency signals.)
3. Leaking of the wave energy into adjacent media such as contained fluids.

1.2 Acoustic Emission in Soils

The basic generators of acoustic emissions in soils are the mechanisms which are responsible for the shear strength of soils. Mobilization of shear strength components within the soil itself and due to the interaction of soil with other adjacent natural or construction materials is directly related to the level of acoustic emission. When soils are stressed, they respond by reorganizing constituent particles and changing their relative positions with the consequent generation of stress waves. This is also the main objective of the AE monitoring techniques, which enables the detection of the occurrence of distress in soil before the development of significant movements.

For granular soils, the shearing resistance, rolling friction and dilatation are the fundamental attributes of AE. In case of cohesive soils, AE activities depend on both friction and cohesion. In soils, frictional components of shear strength are more emittive than the cohesion components. Particle size, shape, gradation, and mineral types also have major roles in the frictional components of the acoustic emission. On the other hand, water content, plasticity, and stress history have major roles in cohesive component of the AE.
1.2.1 Use of Wave-Guides

In most of the non-destructive tests, the transducers are attached directly on the structure being monitored. In soils, on the other hand, attenuation of the elastic waves as they travel through the soil can be relatively high depending on the frequency of the AE waves. Therefore, in soils, installation of wave guides is important to avoid the signal strength losses in detection. Monitoring soils using high frequency AE techniques is largely affected by the high level of attenuation in soils. Since metals have a three to four times of magnitude lower attenuation than soils, metal wave-guides have been found very useful in conducting the signals from within the soil mass to be received by AE sensors. Therefore, the uses of wave-guides to monitor AE in soils have become commonplace (Dixon, 1999).

A wave-guide is a device that couples elastic energy from a structure or other test objects to a remotely mounted sensor during AE monitoring. It is possible to drive the wave-guide into the host soil for short distances. For deeper slopes, it is necessary to install wave-guides in pre-drilled boreholes. The latter method requires a backfill material to improve the contact between the host soil and wave-guide. Depending on the backfill material, two possible systems are available; passive and active wave-guide systems.

For passive systems the annulus around the wave-guide has to be backfilled with low AE activity material such as clays, so the installation does not introduce additional sources of AE into the wave-guide. Any recorded AE signal is assumed to emanate from the deforming host soil itself. Driven wave-guide systems can also be defined as passive as a result of the wave-guide being in direct contact with the in-situ material.

Active wave-guide systems are installed when the monitoring site consists of cohesive material. Since the emission levels generated in such soils are low, it is difficult to obtain strong AE records. Therefore, the annulus can be backfilled with granular soils such as sand or gravel which produce strong AE signals and enhance the original signal. Although the recorded AE data will not relate directly to the stress state of the host soil, it may be possible to calibrate the system, such that the recorded enhanced AE signal can be related to the magnitude of the general ground deformation of the host soil.
Steel tubes are also used for wave-guides and steel threaded rings are used for connecting sections of wave-guides. The choice of the steel tube AE wave-guide has the advantages that it can be easily fabricated to the required cross section and length, and also possesses a low ultrasonic attenuation coefficient. The steel wave-guide system transmits the emission generated by the frictional motion of the soil particles, which are in contact with or close to the wave-guide.

Experiments conducted by Dixon (1999) with two backfill types, gravel and sand, showed that the former backfill was “noisier” under small displacements than the latter. The sand backfill appears to generate low magnitude emission over a long time scale whereas gravel backfill generates high magnitude emission over a short time scale.

In general, the acoustic emission signals obtained using transducers are wide band and consist of broad range of high frequency components and significant time-based characteristics and noise. This condition creates difficulties in visually characterizing the AE signals in a meaningful manner. Therefore, one has to use a sophisticated signal processing method to analyze the non-stationary AE signals. In this regard, the wavelet based multi-resolution approach provides a convenient approach for analyzing transient or time varying signals.

1.3 Research Objectives

The objectives of this research are to
1. detect and record the acoustic emission (AE) signals emitted during the shearing of a cohesionless soils (sand)
2. analyze the recorded AE signals using the wavelet theory and
3. compare the properties of de-noised signals obtained from wavelet analysis with those of Fast Fourier Transformation (FFT).
CHAPTER 2
WAVELET TRANSFORMS APPLIED TO IDENTIFY THE ACOUSTIC EMISION SIGNALS IN SOILS

2.1 Wavelet Transforms

While the Fourier transform deals with transforming the time domain components to the frequency domain and frequency analysis, the wavelet transform deals with scale analysis. The later approach is known as multi-resolution analysis. To approximate choppy signals, for many decades, scientists have wanted more appropriate functions than the sine and cosine (base functions) which comprise Fourier analysis. Scale analysis deals with creating mathematical structures that provide varying time/frequency/amplitude slices for analysis. This transform is a portion or one or a few cycles of a complete waveform, hence the term wavelet.

Figure 2.1 Typical Wavelet Transforms
The wavelet transform has the ability to identify frequency (or scale) components and with their location(s) in a time scale. Additionally, computations are directly proportional to the length of the input signal. In wavelet analysis, the scales play a major role. Wavelet algorithms process data at different scales or resolutions. If one looks at a signal with a large "window", one would notice gross features. Similarly, if one looks at a signal with a small "window," one would notice relatively small discontinuities as shown in Figure 2.1. One way to achieve this is to have short high-frequency fine scale functions and long low-frequency ones.

By definition, sine and cosine functions are non-local stretching out to infinity, and therefore do a poor job in approximating sharp spikes. On the other hand, with wavelet analysis, one can use approximate functions that are contained neatly in finite (time/frequency) domains. Wavelets are well-suited for approximating data with sharp discontinuities. The wavelet analysis procedure usually adopts a wavelet prototype function, called an "analyzing wavelet" or "mother wavelet." Temporal analysis is performed with a contracted, high-frequency version of the prototype wavelet, while frequency analysis is performed with a dilated, low-frequency version of the prototype wavelet. Because the original signal or function can be represented in terms of a wavelet expansion (using coefficients in a linear combination of the wavelet functions), data operations can be performed using only the corresponding wavelet coefficients.

The flexibility of the analyzing wavelet is a major difference between the two types of analyses and is important in determining the results of the analysis. The "wrong" wavelet may be no better (or even far worse than) than the Fourier analysis. Hence a successful application presupposes some expertise on the part of the user. Some prior knowledge about the signal must generally be available in order to select the most suitable distribution and adapt the parameters to the signal. Some of the most common wavelet types are shown in Figure 2.2.
2.2 Comparison of Wavelet Analysis with Fourier Analysis

While a typical Fourier transform provides frequency content information for samples within a given time interval, a perfect wavelet transform records the start of one frequency (or event), and then the start of a subsequent event with amplitude added to or subtracted from the base event. The main disadvantage of a Fourier transform is that it has only frequency resolution and no time resolution which means that although one might be able to determine all of the frequencies present in a signal; one would not know at what time they appear.

In wavelet analysis on the other hand, the use of a fully scalable modulated window solves the signal-cutting problem. The window is shifted along the signal and for every position the spectrum is calculated. Then this process is repeated many times with a slightly shorter (or longer) window for every new cycle. In the end the result will be a collection of time-frequency representations of the signal, all with different resolutions. Because of this collection of representations one can speak of a multi-resolution analysis. In the case of wavelets one normally does not speak about time-frequency representations but about time-scale representations.
2.3 The Continuous Wavelet Transform

Mathematically, the process of Fourier analysis is represented by the Fourier transform:

\[ f(w) = \int_{-\infty}^{\infty} f(t) e^{-jwt} dt \]  

(2.1)

Which is the sum over the entire time domain of the signal \( f(t) \) multiplied by a complex exponential which contains sine and cosine functions. The results of the transform are the Fourier coefficients \( f(w) \), which when multiplied by the corresponding sinusoid of frequency yield the constituent sinusoidal components of the original signal. Graphically, the transformation process can be shown as in Figure 2.3.

![Figure 2.3 Illustration of Fourier Transforms](image)

Similarly, the continuous wavelet transform (CWT) is defined as the sum over the entire time of the signal multiplied by scaled, shifted versions of the wavelet function \( \psi(t) \) (Equation (2.3)). The results of the CWT are many wavelet coefficients \( C_{s,\tau} \) (Equation (2.2)), which are functions of scale and position. When using a real function,

\[ C_{s,\tau} = \int_{-\infty}^{\infty} f(t) \psi_{s,\tau}(t) dt \]  

(2.2)
\begin{equation}
\Psi_{r,s}(t) = \frac{1}{\sqrt{|s|}} \psi \left( \frac{t-\tau}{s} \right) \tag{2.3}
\end{equation}

\(\psi_{r,s}\) is the mother wavelet used for scaling and translation. The variables \(s\) and \(\tau\) are scale factor and translation factor respectively. The primary requirements of the \(\psi(t)\) are that the integral of the wavelet over the entire time domain must be zero (Equation (2.4)) and square integral of \(\psi(t)\) must satisfy the admissibility condition (Equation (2.5)).

\begin{equation}
\int_{-\infty}^{\infty} \psi(t) \, dt = 0 \tag{2.4}
\end{equation}

\begin{equation}
\int_{-\infty}^{\infty} \left| \psi(t) \right|^2 \, dt < \infty \tag{2.5}
\end{equation}

Shifting a wavelet simply means delaying or hastening its onset. Mathematically, delaying a function \(f(t)\) by \(\tau\) is represented by \(f(t-\tau)\). Figure 2.4 illustrates the wavelet \(\psi(t)\) and shifted wavelet \(\psi(t-\tau)\).

![Wavelet function](image)

**Figure 2.4 Effect of Shifting**

Multiplying each coefficient by the appropriately scaled and shifted wavelet yields the constituent wavelets of the original signal \(f(t)\) (Equation (2.6)).

\begin{equation}
f(t) = \int \int C_{s,\tau} \Psi_{s,\tau}(t) \, ds \, d\tau \tag{2.6}
\end{equation}

10
2.4 Scaling

Scaling allows one to either narrow down the frequency band of interest, or determine the frequency content in a narrower time interval. As illustrated in Figure 2.5, scaling a wavelet simply means stretching or compressing it. Mathematically this can be achieved by introducing a scale factor often denoted by “a”. For example, the effect of the scale factor on sinusoids is seen in Figure 2.6.

![Figure 2.5 Illustration of Wavelet Transforms](image)

**Figure 2.5 Illustration of Wavelet Transforms**

![Figure 2.6 Effect of Scale Factors on Sinusoids](image)

**Figure 2.6 Effect of Scale Factors on Sinusoids**

The scale factor “a” is applicable to wavelets in a similar way. The smaller the scale factor, the more "compressed" the wavelet is.
It is clear from Figures 2.6 and 2.7 that, for a sinusoid \( \sin(\omega t) \), the scale factor is inversely related to the radian frequency \( \omega \). Similarly, with wavelet analysis, the scale is related to the frequency of the signal.

2.5 Sequence of Steps to Obtain a Continuous Wavelet Transform (CWT)

As shown in Equation (2.2) the continuous wavelet transform is the sum of the segments of the original signal multiplied by scaled, shifted versions of the wavelets over the entire time domain of the signal. This process produces wavelet coefficients that are functions of scale and position.

The following are the steps to be followed in creating a CWT:

1. Consider a given wavelet and compare it to a section at the start of the original signal.
2. Calculate a number, \( C \), that represents how closely correlated the wavelet is with this section of the signal. The higher \( C \) is, the higher the correlation is. More precisely, if the signal energy and the wavelet energy are equal to one, \( C \) may be interpreted as a correlation coefficient.

It must be noted that the results will depend on the shape of the wavelet one chooses (Figure 2.2).
3. Shift the wavelet to the right and repeat steps 1 and 2 until one has covered the entire signal (Figure 2.9).

4. Change the scale (stretch) of the wavelet (Figure 2.10) and repeat steps 1 through 4.

5. Repeat steps 1 through 4 for all selected scales.
When the entire process is complete, one has the coefficients produced at different scales by different sections of the signal. The coefficients represent the results of regression of the original signal performed on the wavelets.

2.6 Relationship Between Scale and Frequency

The higher scales correspond to the most "stretched" wavelets. The more stretched the wavelet, the longer the portion of the signal with which it is being compared, and thus the coarser the signal features being measured by the wavelet coefficients.

![Figure 2.11 Different Scale Wavelets](image)

Thus, the following correspondence exists between wavelet scales and frequency as revealed by wavelet analysis:

- Low scale corresponds to a compressed wavelet. It is useful for rapidly changing details and high frequency ($\omega$).
- High scale corresponds to a stretched wavelet. It is useful for slowly changing coarse features and low frequency ($\omega$).

2.7 The Discrete Wavelet Transform

Calculating the wavelet coefficients at every possible scale using continuous wavelet transform (CWT) is a tedious exercise that generates excessive data. To overcome this problem and get a manageable count of data, discrete wavelets have been introduced. Discrete wavelets can only be scaled and translated in discrete steps. This can be achieved by modifying the mother wavelet representation in Equation (2.3) to Equation (2.7).
\[ \Psi_{j,k}(t) = \frac{1}{\sqrt{s_0'}} \Psi\left( \frac{t - k\tau_0 s_0'}{s_0'} \right) \] (2.7)

Where \( j \) and \( k \) are integers and \( s_0 (> 1) \) is a fixed dilation step. In general, the translation factor \((\tau_0)\) depends on the dilation step. A common choice for \( s_0 \) and \( \tau_0 \) are 2 and 1 respectively (Equation (2.8)), which lead to a dyadic sampling grid.

\[ \Psi_{j,k}(t) = 2^{-j} \Psi\left(2^{-j} t - k \right) \] (2.8)

Then, the discretized wavelet transform (DWT) pair can be given in Equation (2.9).

\[ d_{j,k} = \int f(t) \Psi_{j,k}(t) dt \] (2.9)

Where \( d_{j,k} \) are the discrete wavelet transform values given on a scale-location grid of indices \( j, k \). For the discrete wavelet transform, the values \( d_{j,k} \) are known as wavelet coefficients or detail coefficients. An arbitrary signal \( f(t) \) can be reconstructed by summing the orthogonal wavelet basis functions, weighted by the wavelet transform coefficients \( d_{j,k} \).

\[ f(t) = \sum_{j=-\infty}^{\infty} \sum_{k=-\infty}^{\infty} d_{j,k} \Psi_{j,k}(t) \] (2.10)

Orthonormal dyadic discrete wavelets are associated with scaling functions and their dilation equations. The scaling function \((\phi)\) is associated with smoothing of the signal and has the same form as the wavelet, given by

\[ \phi_{j,k}(t) = 2^{-j} \phi(2^{-j} t - k) \] (2.11)
They have the property

\[ \int_{-\infty}^{\infty} \phi_{0,0}(t) dt = 1 \]  \hspace{1cm} (2.12)

Where \( \phi_{0,0}(t) = \phi(t) \) is sometimes referred to as the father scaling function or father wavelet. The scaling function is orthogonal to translations of itself, but not to dilations of itself. The scaling function can be convolved with the signal to produce approximation coefficients as follows:

\[ a_{j,k} = \int f(t) \phi_{j,k}(t) dt \]  \hspace{1cm} (2.13)

A continuous approximation of the signal at scale \( j \) \((f_j(t))\) can be generated by summing a sequence of scaling functions at this scale factored by the approximation coefficients as follows:

\[ f(t) = \sum_{k=-\infty}^{\infty} a_{j,k} \phi_{j,k}(t) \]  \hspace{1cm} (2.14)

Figure 2.12(a) shows a simple scaling function together with two of its corresponding dilations at that location. Figure 2.12(b) shows one period of a sine wave, contained with a window. Figure 2.12(c) shows various approximation of the sine wave generated using Equations (2.13) and (2.14).
One can represent a signal \( f(t) \) using a combined series expansion using both the approximate coefficients and the wavelet (detail) coefficients as follows:

\[
f(t) = \sum_{k=-\infty}^{\infty} a_{j_0,k} \phi_{j_0,k}(t) + \sum_{j=0}^{\infty} \sum_{n=-\infty}^{\infty} d_{j,k} \Psi_{j,k}(t)
\]  

\( (2.15) \)
Figure 2.13 How an Infinite Set of Wavelets is Replaced by One Scaling Function

A more detailed theory on multi-resolution analysis can be found in Addison (2002).

2.8 One-Stage Filtering: Approximations and Details

Elimination of noise is a central part for the application of wavelet algorithms. The frequency filter is used to eliminate unwanted frequency ranges and matches the measurement chain to the requirements of the application. For many signals, the low-frequency content is the most important part which gives the signal its identity. The high-frequency content, on the other hand, imparts flavor or nuance. Considering the human voice, if one removes the high-frequency components, the voice sounds different, but one can still tell what is being said. However, if one removes enough of the low-frequency components, one hears gibberish.

In wavelet analysis, filtering is performed to separate approximations (A) and details (D). The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components. The filtering process, at its most basic level, can be illustrated in Figure 2.14.
In Figure 2.14 the original signal, S, passes through two complementary filters and emerges as two signals. Unfortunately, if one actually performs this operation on a real digital signal with 1000 samples, then the resulting signals will each have 1000 samples, for a total of 2000 (Figure 2.15). By observing the computation carefully, one may keep only one data point out of two in each of the two 1000-length samples to obtain the complete information. This is the notion of down sampling in which one produces two sequences called cA and cD (Figure 2.16). These are also called discrete wavelet transform coefficients.
As an example, a one-stage discrete wavelet transform of a signal will be a pure sinusoid with high-frequency noise added to it. A schematic diagram with real signals inserted into it is shown in Figure 2.17.

It is noticed that the detail coefficients cD are small and consist mainly of a high-frequency noise, while the approximation coefficients cA contain much less noise than does the original signal. One may observe that the actual lengths of the detail and approximation coefficient vectors are slightly more than half the length of the original signal. This has to do with the filtering process, which is implemented by convolving the signal with a filter. Thus the convolution "smears" the signal, introducing several extra samples into the result.
2.9 Multiple-Level Decomposition

Wavelet transform is constituted by different levels. The major factor that affects the number of levels one can reach to achieve the satisfactory noise removal results is the signal-to-noise (SNR) in the original signal. Generally, the signals from the piezoelectric sensors have higher SNR. Therefore, to process the acoustic emission data, one needs more levels of wavelet transform to remove most of its noise. The decomposition process can be carried out so that one signal is broken down into many lower resolution components. This process is called the multi-level decomposition and the product is termed the wavelet decomposition tree.

![Figure 2.18 Multiple Level Decomposition](image)

The wavelet decomposition tree of a signal can yield valuable information regarding the signal. Noise in the signal is captured in the detail coefficients, particularly in the small coefficients at higher levels in the decomposition. By zeroing or shrinking these coefficients, one can get smoother reconstructions of the input signal. This is done by specifying a threshold value for each level of detail coefficients and then zeroing or shrinking all the detail coefficients below this threshold value.
Figure 2.19 Multilevel Filtering

The coefficients $c_{A1}$, $c_{A2}$ and $c_{A3}$ shown in Figures 2.18 and 2.19 are the approximate coefficients computed using the wavelet analysis at level 1, level 2 and level 3 respectively. Similarly, the coefficients $c_{D1}$, $c_{D2}$ and $c_{D3}$ are the detail coefficients computed using the wavelet analysis at level 1, level 2 and level 3 respectively.

It has been explained above how the discrete wavelet transform can be used to analyze, or decompose signals. This process is called the decomposition or analysis. The other half of the story is how those components can be assembled back into the original signal without loss of information (Figure 2.20). This process is called the reconstruction, or synthesis. The mathematical manipulation that effects synthesis is called the inverse discrete wavelet transforms (Equation 2.15).

Figure 2.20 Reconstruction of Signal
This chapter explains both continuous wavelet transform and discrete wavelet transform. However, due to large amount of discrete and non-stationary AE data obtained in this study, a fast algorithm is needed to analyze the data. Therefore, the particular technique of discrete wavelet transform (DWT) is selected for acoustic emission data analysis in Chapter 4.

2.10 Numerical Example

2.10.1 The Forward Transform

The forward Haar wavelet transform can be described in terms of averaging and differencing adjacent pairs of data values at a sequence of geometrically increasing levels. The computation of averages (approximate coefficients) and differences (detail coefficients) can be obtained using Equations 2.9, 2.14, 2.16 and 2.17.

Haar mother wavelet $\psi(t)$:

\[
\psi(t) = \begin{cases} 
1 & 0 \leq \langle t \rangle \leq \frac{1}{2} \\
-1 & -1 \leq \langle t \rangle < 1 
\end{cases}
\]  

(2.16)

Haar scaling function $\phi(t)$:

\[
\phi(t) = \begin{cases} 
1 & 0 \leq \langle t \rangle < 1 \\
0 & \text{otherwise}
\end{cases}
\]  

(2.17)

Practically, if a data set \(\{s_0, s_1, \ldots, s_{N-1}\}\) contains \(N\) elements, there will be \(N/2\) approximate coefficients \(a_i\) (averages) and \(N/2\) detail coefficients \(d_i\) (differences) (Addition, 2002). The averages become the input for the next level in the decomposition calculation. The recursive iterations continue until a single average and a single coefficient are calculated. One can derive the Equations (2.18) and (2.19) using the Equations (2.9), (2.14), (2.16) and (2.17) to compute the coefficients from an odd and even element in the data set.
where, $s_i$ and $s_{i+1}$ are the $i^{th}$ and $(i+1)^{th}$ elements in the data set respectively.

Table 2.1 A Sample Acoustic Emission Data

<table>
<thead>
<tr>
<th>Sample No.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Signal (mV)</td>
<td>37</td>
<td>35</td>
<td>28</td>
<td>28</td>
<td>58</td>
<td>18</td>
<td>21</td>
<td>15</td>
</tr>
</tbody>
</table>

Table 2.1 shows a sample data set consisting of acoustic emission signals in mV. Considering the sample data from Table 2.1 and using the Equations (2.18) and (2.19), the approximate coefficients ($a_i$) and detail coefficients ($d_i$) are computed as follows:

First select two adjacent odd and even elements.

Let $s_i = 37$ and $s_{i+1} = 35$

Using Equation (2.18) and the selected data of $s_i$ and $s_{i+1}$, the approximate coefficient ($a_i$) is computed as follows:

$$a_i = \frac{s_i + s_{i+1}}{2} = \frac{37 + 35}{2} = 36$$

Similarly using the Equation (2.19) and the selected data of $s_i$ and $s_{i+1}$, the detail coefficient ($d_i$) is computed as follows:

$$d_i = \frac{s_i - s_{i+1}}{2} = \frac{37 - 35}{2} = 1$$
Table 2.2 represents the completed transformation of the data set in Table 2.1.

The first row in Table 2.2 is the original signal. The second row in Table 2.2 is generated by using Equations (2.18) and (2.19). The coefficients computed using Equation (2.18) are written in the first four places and the coefficients computed using Equation (2.19) are written in the remaining four places consecutively. Computations are repeated on the approximate coefficients while the detail coefficients are retained in each step.

<table>
<thead>
<tr>
<th>Signal (mV)</th>
<th>37</th>
<th>35</th>
<th>28</th>
<th>28</th>
<th>58</th>
<th>18</th>
<th>21</th>
<th>15</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level (1)</td>
<td>36</td>
<td>28</td>
<td>38</td>
<td>18</td>
<td>1</td>
<td>0</td>
<td>20</td>
<td>3</td>
</tr>
<tr>
<td>Level (2)</td>
<td>32</td>
<td>28</td>
<td>4</td>
<td>10</td>
<td>1</td>
<td>0</td>
<td>20</td>
<td>3</td>
</tr>
<tr>
<td>Level (3)</td>
<td>30</td>
<td>2</td>
<td>4</td>
<td>10</td>
<td>1</td>
<td>0</td>
<td>20</td>
<td>3</td>
</tr>
</tbody>
</table>

Approximate Coefficients (aₖ) | Detail Coefficients (dₖ)

2.10.2 The Inverse Transform

One can derive the Equations (2.20) and (2.21) using the Equations (2.15), (2.16) and (2.17) to reconstruct the original and truncated signals. As shown in Equation (2.20), the iᵗʰ approximate coefficient (aᵢ) and the iᵗʰ detail coefficient (dᵢ) are added to reconstruct the iᵗʰ data (sᵢ) in a particular level. These aᵢ and dᵢ are computed using the forward transform described in Section 2.7.

\[ sᵢ = aᵢ + dᵢ \]  \hspace{2cm} (2.20)

\[ sᵢ+₁ = aᵢ - dᵢ \]  \hspace{2cm} (2.21)

Considering the transformed data in level (1) from Table 2.2 and using the Equations (2.20) and (2.21), the original data \( sᵢ \) and \( sᵢ₊₁ \) are computed respectively. For example, select an approximate coefficient (aᵢ) and the corresponding detail coefficient (dᵢ) as follows:
Let $a_i = 36$ and $d_i = 1$

Using the Equation (2.20) and the selected coefficients of $a_i$ and $d_i$, the original data ($s_i$) is computed as follows:

$$s_i = 36 + 1 = 37$$

Similarly using the Equation (2.21) and the selected coefficients of $a_i$ and $d_i$, the original data ($s_{i+1}$) is computed as follows:

$$s_{i+1} = 36 - 1 = 35$$

From these sample calculations one can understand how the Haar wavelet transforms work in cases of decomposition and reconstruction. By continuing this decomposition until a single approximate coefficient and a single detail coefficient are calculated, one can obtain the complete transformation of the sample data as shown in Table 2.2.

2.10.3 Thresholding Decomposed Signal

The process of thresholding is carried out on detail coefficients. There are many methods for setting the threshold. The most time-consuming way is to set the threshold limit on a case-by-case basis. The limit is selected such that satisfactory noise removal is achieved. For a particular threshold value, the detail coefficients in Table 2.2 which are less than or equal to that particular threshold value are replaced by zeros.

Consider a threshold of 2 for this transform. Thus, detail coefficients which are less than 2 or equal to 2 become 0 as shown in the level 3 of Table 2.3. These updated values are shown in blue-shaded cells. Once the thresholding is completed, one can reconstruct the signal using Equations (2.20) and (2.21) from the coefficients in the level (3T) of Table 2.3.

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Repetitions of the above reconstruction procedure with threshold value of 3, 4, and 10 yield results shown in Tables 2.4 - 2.6.
### Table 2.6 Reconstruction of Data Using a Threshold Value 10

<table>
<thead>
<tr>
<th>Level (3)</th>
<th>30</th>
<th>2</th>
<th>4</th>
<th>10</th>
<th>1</th>
<th>0</th>
<th>20</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Set Zeros with a Threshold Value 10</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Level (3T)</td>
<td>30</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>20</td>
<td>0</td>
</tr>
<tr>
<td>Level (2)</td>
<td>30</td>
<td>30</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>20</td>
<td>0</td>
</tr>
<tr>
<td>Level (1)</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>0</td>
<td>0</td>
<td>20</td>
<td>0</td>
</tr>
<tr>
<td>Filtered signal (mV)</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>50</td>
<td>10</td>
<td>30</td>
<td>30</td>
</tr>
</tbody>
</table>

Finally, Figure 2.28 graphically represents the original signal (Table 2.1) and the filtered signals obtained from Tables 2.3 - 2.6 with different threshold values.

![Figure 2.21 Plots of Original and Filtered Signal](image)

As shown in Figure 2.21, the smaller threshold values 2, 3 and 4 smoothen the small peak values with no significant change in the wave pattern. Also, no significant change occurs on the maximum peak value of original signal. On the other hand, the threshold value 10 not only changes the peak value significantly but also changes the
wave pattern of the original signal. From these results, one can conclude that the selection of an appropriate threshold value is a vital step in the filtering process.
CHAPTER 3
EXPERIMENTAL SETUP AND DATA COLLECTION

3.1 Introduction
This section describes the details of the different experimental setups and shearing conditions under which acoustic emission data was collected.

3.2 Shearing Procedure
A 12” × 12” × 16” wooden shear box (Figures 3.1 and 3.2) was constructed for inducing direct shear on a sand sample. To maintain a constant rate of shear, an electric screw jack was first attached to the upper half of the shear box (Figure 3.1). The operation of electric jack created noise which made it difficult to differentiate the actual AE signals due to the shearing from the total AE signals that contained the surrounding noise. In order to avoid this problem, the electric screw jack was replaced by a manually operated screw jack (Figure 3.2). Approximate constant shearing rates of one cycle of revolution of the screw jack per twenty seconds and one cycle of revolution of the screw jack per ten seconds were respectively used in “slow” and “fast” shearing modes.

Figure 3.1 Shear Box with Electric Screw Jack
Figure 3.2 Shear Box with Manual Screw Jack

Figure 3.3 Universal Micro-Tribometer

Figure 3.4 Mote Acoustic Emission Sensors with Circuit Board
The following steps were used for the data collection process:

1. The bottom part of shear box was filled with sand placed in successive layers. Each layer was compacted using surface vibration.
2. The sensor was laid just below the shear plane. Then sand was filled up to the top of the shear box with frequent surface vibration.
3. Approximately 80 lbs of surcharge was applied on the sand.
4. The built-in sensor circuits were removed from the universal Micro Tribometer (Fig. 3.3) and the external AE sensor circuit board (Fig. 3.4) was connected to the above machine.
5. To collect continuous AE signals, the UMT-2 system software was set up.
6. The vertical pins from the shear box were removed and then the manual screw jack was operated with an approximate constant rate.
7. The AE data saved in the computer was downloaded as text files.

3.3 Data Acquisition

Two different data acquisition systems were employed to acquire the acoustic emission signals.

In the first data acquisition system the following instruments were used:

1. PCS64i Oscilloscope (Figure 3.5)
2. Wideband AE Sensors (Figure 3.6)
3. Wooden Shear Box (12"x12" x16") (Figure 3.2)
4. Computer

Because of the following difficulties encountered in the above experimental setup, an alternative (second) option was selected to complete the task.

1. Noise created by instrumentation itself
2. Noise created by connectors
3. Unsupportive software platform (DOS) to record the transient signals
4. Need for a higher triggering value
In the second data acquisition system the following instruments were used:

1. Universal Micro-Tribometer (Figure 3.3)
2. Mote-Sensor with circuit board (Figure 3.4)
3. Wooden Shear Box (12”x12” x16”) (Figure 3.2)
4. Computer

3.3.1 PCS64i Oscilloscope

In the first experimental setup, a PCS64i digital storage oscilloscope (Figure 3.5) was used to observe the signals which were obtained from two different types of wide band sensors designed for acoustic emission monitoring. They are D9204 and ISR3 bought from Physical Acoustics Corporation. During the first stage of the experimental process, along with the PCS64i digital storage oscilloscope and the above two types of acoustic emission sensors, a band pass filter, the wooden shear box (Figure 3.2) and a computer with Microsoft Windows 98 platform were used.

The PCS64i is a digital storage oscilloscope which uses a compatible computer and its monitor to display acquired waveforms. All standard oscilloscope functions are available in the supplied DOS or Windows programs. Its operation resembles that of a normal oscilloscope with the difference that most operations in the former can be performed using the mouse. Apart from its use as an oscilloscope, the unit can also be used as a spectrum analyzer up to 16 MHz, and also as a transient signal recorder for recording voltage variations for the comparison of two voltages over a longer period. The oscilloscope and transient recorder operations can be performed on two completely separated channels with a sampling frequency up to 32 MHz in real time.

(a) Front  
(b) Rear  
Figure 3.5 PCS64i, Digital Storage Oscilloscope
3.3.2 Acoustic Emission Piezoelectric Sensors

The AE sensor is a detection device such as a piezoelectric transducer that transforms the particle motion produced by an elastic wave into an electrical signal. The piezoelectric sensor consists of a piezoelectric element encapsulated in extruded aluminum housing. Since piezoelectric sensors are the most appropriate for AE testing, virtually all acoustic wave devices and sensors use piezoelectric material. They are also robust and more sensitive than other sensing techniques. Since the AE signals are relatively weak, a preamplifier is generally connected to the sensor to minimize the noise interference and prevent the signal loss. Sometimes, the sensor and the preamplifier are built as one unit.

The acoustic properties of the medium where the measurement is made are very important in the design and selection of appropriate transducers. Transducers must also withstand the severe effects of weather changes, biological activity, hydrostatic pressure, and extreme temperature conditions.

AE sensors are either single-ended (S) or differential (D) in construction. The single-ended design employs a single crystal to provide high sensitivity and omnidirectional response to the AE excitation regardless of orientation. The differential designs provide common mode rejection of unwanted signals in environments of high electromagnetic interference. Common-mode rejection is the ability of a balanced (or differential) input to reject the part of the incoming signal which has the same amplitude and phase on both input terminals, referenced to ground. Hence this is the ability to respond to only differences at the input terminals.

The sensors used in the first experimental setup are wideband, differential and piezoelectric with a integral cable (Figure 3.6). Wideband sensors are typically used in research applications or other applications where a high fidelity AE response is required. In research applications where frequency analysis of the AE signal is required, wideband AE sensors are useful in helping determine the predominant frequency band of AE sources for noise discrimination and selection of a suitable lower cost, general purpose AE sensor. In high fidelity applications, various AE wave-modes can be detected using
wideband sensors, thus providing more information about the AE source and distance of the AE event.

In the second experimental setup, an AE piezoelectric mote-sensor was used in conjunction with the Universal Micro-Tribometer (Figure 3.3). The later has been manufactured to monitor the nanomachining process including the delamination defects.

![Wide Band Acoustic Emission Sensors](image)

**Figure 3.6 Wide Band Acoustic Emission Sensors**

### 3.3.3 Universal Micro-Tribometer (UMT)

This multi-specimen test system (Figure 3.3) has been developed for studying the chemical mechanical planarization (CMP). It is equipped with acoustic emission (AE) and coefficient of friction (CoF) sensors and the required data acquisition systems. During the current experimental process, these built-in AE and friction sensors were disconnected from the data acquisition systems and an external AE sensor with the circuit board (Figure 3.4) was connected to the data acquisition systems.

In each trial, AE data were collected and downloaded in the text format. Several tests were completed using the above test setup with horizontal and vertical placement of the sensor as well as different rates of shearing. Table 3.1 provides the designations used to identify different testing conditions.
### Table 3.1 Test Designations

<table>
<thead>
<tr>
<th>Placement of Sensor</th>
<th>Rate of Shearing</th>
<th>Test Designation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Horizontal Placement of Sensor</strong></td>
<td>Fast</td>
<td>HF1, HF2, HF3</td>
</tr>
<tr>
<td></td>
<td>Slow</td>
<td>HS1, HS2</td>
</tr>
<tr>
<td></td>
<td>No Shear</td>
<td>HNS</td>
</tr>
<tr>
<td><strong>Vertical Placement of Sensor</strong></td>
<td>Fast</td>
<td>VF1, VF2</td>
</tr>
<tr>
<td></td>
<td>Slow</td>
<td>VS1, VS2</td>
</tr>
<tr>
<td></td>
<td>Normal</td>
<td>VN</td>
</tr>
<tr>
<td></td>
<td>No Shear</td>
<td>VNS</td>
</tr>
</tbody>
</table>
CHAPTER 4
ANALYSIS OF DATA

4.1 Introduction

This chapter describes the methods used to analyze the acoustic emission (AE) data collected from Universal Micro Tribometer (UMT) (Chapter 3). The concepts of wavelets and Fast Fourier Transform are the two primary methods used for data processing. First, the wavelet theory was used for de-noising the acoustic emission signals and then the de-noised signals were compared with the similarly de-noised signals obtained using Fourier analysis.

Data obtained from the AE mote-sensor was saved in the computer and then downloaded into text files. These text files are given in the Appendix A. The downloaded text format data are transformed into Excel spreadsheets and used for the analysis. For signal processing, MATLAB built-in functions with codes developed by the author have been used. Most of the common mother wavelet functions (Section 2.1), used for data analysis with different levels, are built-in with the MATLAB wavelet toolbox. Data were analyzed using discrete wavelet transform with Daubechies mother wavelet and scale functions (Addison, 2002).

Figures 4.1 to 4.3 are the sample plots of downloaded data obtained under different conditions. Figures 4.1 and 4.2 illustrate the plot of acoustic emission with noise versus time obtained with the horizontal and vertical placement of the mote-sensor during the process of shearing respectively. Figure 4.3 shows the data obtained under the same experimental setup with no shear condition. These plots are compared in detail in Section 4.4.
Figure 4.1 Data Obtained with Horizontal Placement of Mote-Sensor (Shearing Rate: Fast) – HF1

Figure 4.2 Data Obtained with Vertical Placement of Mote-Sensor (Shearing Rate: Normal) - VN

Figure 4.3 Data Obtained Under No Shear Condition
4.2 Use of the MATLAB Wavelet Toolbox for Acoustic Emission Signal Processing

The Wavelet Toolbox extends the MATLAB® technical computing environment with graphical tools and command-line functions for developing wavelet-based algorithms for the analysis, de-noising, and compression of signals. Wavelet analysis provides more precise information about signal data than other signal analysis techniques, such as the Fourier transforms.

The Wavelet Toolbox supports the interactive exploration of wavelet properties and 1-D and 2-D applications in communications and geophysics. The Wavelet Toolbox supports a full suite of wavelet analysis and synthesis operations listed below:

- Achieve high rates of signal or image compression with virtually no loss of significant data
- Restore noisy signals
- Discover trends in noisy or faulty data
- Study the fractal properties of signals
- Extract information-rich features for use in classification and pattern recognition applications

The following figures illustrate the major steps followed during the data analysis using MATLAB. The startup window is shown in Figure 4.4.

![Figure 4.4 Startup Window of the MATLAB Program to Select Wavelet Tool Box](image-url)
After selecting the wavelet tool box the window in Figure 4.5 will appear on the screen. From this window, one can have two selections for 1D with different graphical options such as wavelet 1-D and wavelet packet 1-D. The data must be in the “mat” format in order to import them into the MATLAB tool box. Using the MATLAB codes developed by the author, the data transferred into the excel sheet is first changed into the “mat” format.

In the literature, several wavelet basis functions such as Haar’s, Daubechies, Coiflets and Symmlets, etc. are available. One should select the “mother wavelet” carefully to approximate and capture the transient spikes of the original signal. “Mother wavelet” will not only determine how well one estimates the original signal in terms of the shape of the spikes, but also, it will affect the frequency spectrum of the de-noised signal. Some of the desirable properties of the basis functions are good time-frequency
localizations, various degrees of smoothness and large number of vanishing moments. Although the Haar wavelet algorithm has the advantage of being simple to compute with compact support, and easier to understand, it does not have better time frequency localization. Further, it is unsuitable for representing classes of smoother functions due to its discontinuities. The Daubechies algorithm has a slightly higher computational overhead and is conceptually more complex. Since the transformation using the Daubechies mother wavelet overlaps between the iterations, that overlap allows the Daubechies algorithm to pick up detail that is missed by the Haar wavelet algorithm. The most widely used wavelet is the Daubechies’ basis function. The Haar’s filter is best suited to represent step signals or piecewise constant signals whereas the Daubechies’ filter is better for smoother signals.

![Figure 4.6 Plot of Daubechies Mother Wavelet Function (db5)](image)

**Figure 4.6 Plot of Daubechies Mother Wavelet Function (db5)**

Figures 4.6 to 4.11 illustrate a sample test data processing procedure using the abovementioned graphical options. In this signal processing, the Daubechies mother wavelet (db5) and scale functions with level five are used.
Figure 4.7 Plot of Daubechies (5) Scale Function

Figure 4.8 Loaded Original Acoustic Emission Signal Obtained in HS2 with the Horizontal Placement of Mote-Sensor
Using the dialog box shown in the Figure 4.8, one can select the wavelet mother function and the number of levels required to analyze the signal. Once the analysis is completed using the selected mother wavelet, the same dialog box can be used for the de-noising process. Using different display modes, one can view the different modes of synthesized signal to define the threshold values. Defining an appropriate threshold value is one of the crucial steps involved in the de-noising process. Therefore, the user has to carefully review the synthesized signal and adjust the threshold value in order to omit the loss of any useful information.

Figure 4.9 Wavelet Tree and Approximation at Level Five Obtained for HS2 with the Horizontal Placement of Mote-Sensor

Figure 4.9 is one of the built-in display windows used to verify the approximate plot of the signal at level five. By changing the number of levels and the mother wavelet, one can refine the approximate synthesized signal based on judgment. De-synthesis of the signal (s) into $a_i$ and $d_i$ coefficients (Figure 4.9) is described in detail in Chapter 2 (Section 2.7).
Figure 4.10 Approximate and Detail Coefficient Plot for Test 5 with the Horizontal Placement of Mote-Sensor

The options shown in Figure 4.10 can be used to obtain the compressed and denoised signals.
Finally, Figure 4.11 is used to adjust the threshold values during the de-noising process. One can adjust the threshold value by observing the plots for detail coefficients in order to anticipate with the rapid variations. Figure 4.12 illustrates the de-noised signal obtained using MATLAB tool box with wavelet analysis.
4.3 Fast Fourier Transformation Using MATLAB

As part of the objectives of this research, the AE signals were analyzed using Fast Fourier Transforms and compared with the corresponding analysis obtained from wavelet transformation. MATLAB built-in codes and codes developed by the author have been used to complete task.

The following steps were followed in the Fast Fourier Transformation (FFT):

1. Export the signals into Excel spreadsheet and rearrange them into column vector (X).
2. Load the vector (X) using the MATLAB programming language.
3. Obtain the FFT of the loaded data (X) and obtain the results of the transformed complex vector (Y).
4. Calculate the magnitude of the complex vector (Y).
5. Plot the estimated magnitudes of the complex vector versus frequency (Figure 4.13).
6. From the plot in step 5, identify the range which should be removed from the transformation.

Figure 4.12 Plot of De-noised Signal for HS2
7. Replace the selected range of the complex vectors (Y) with zeros.
8. Obtain inverse Fourier transform (Z).
9. By obtaining the real part of vector (Z), reconstruct the de-noised signal (Figure 4.14).

Among the steps described above, the step 7 is the most important one. Using FFT, a signal is transformed from the time domain to the frequency domain. In the frequency domain, the low frequency components contain most of the information (approximation). This is shown by the large peak in the amplitude envelope (Figure 4.14), calculated from the transformed signal. On the other hand, the background noise from surrounding is wide band, dominated by high frequency components. This is shown by small peak in the amplitude envelope (Figure 4.14) calculated from the transformed signal. If the signal does not contain any background noise, the amplitude envelope of high frequency component of the signal is very close to zero. Therefore, the selection of an appropriate range of the transformed vector (Y) using Figure 4.14 to introduce zeros in a certain frequency range is a crucial step in order to omit the loss of useful information. Power spectral density (Figure 4.13) is one of the useful methods to select the dominant frequencies of a signal.

![Figure 4.13 Sample Plot of Power Spectral Density Versus Frequency](image)
Figure 4.14 Magnitude of Transformed Complex Vector Versus Frequency (Identity Test HS2)

Figure 4.15 Sample Filtered Signal Using FFT (Identity Test HS2)
4.4 Comparison of Filtered Signals Obtained Using Wavelet with that of FFT

All the test data obtained from shearing the soil with the horizontal and vertical placement of AE mote-sensor are de-noised using both the wavelet transform and FFT. Figures 4.16 to 4.21 illustrate the comparison of de-noised signals obtained with horizontal placement of sensor and Figures 4.24 to 4.29 illustrate the comparison of de-noised signals obtained with vertical placement of the sensor.

![Figure 4.16 De-noised Signal Using Wavelet and FFT (Test HF1)](image1)

![Figure 4.17 De-noised Signal Using Wavelet and FFT (Test HF2)](image2)
Figures 4.16 to 4.18 illustrate the de-noised signals obtained with a relatively fast rate of shearing with horizontal placement of sensor. Signals de-noised using FFT and wavelets follow the same pattern. In all three tests, the maximum positive peak AE value occurs within the first 35 seconds of the testing period. Also, the maximum peak values are higher than 0.5V.

Figure 4.19 De-noised Signal Using Wavelet and FFT (Test HS1)
Figures 4.19 to 4.20 illustrate the de-noised signals obtained with a relatively slow rate of shearing with horizontal placement of sensor. Signals de-noised using FFT and wavelet follow the same pattern. In both tests, the maximum positive peak AE value occurs after 40 seconds of the testing period. Also, the maximum peak values are higher than 0.03V.

Figure 4.21 illustrates the de-noised signals obtained with no shearing with horizontal placement of the sensor. In this case, the maximum peak value is less than 0.02V. It is observed that there is a significant difference in terms of AE peak value obtained with and without shearing. Under no shear condition, there is no visible AE peak activities recorded.
Figure 4.22 AE Signals Obtained with Horizontal Placement of the Sensor Filtered Using Wavelet Analysis

Figure 4.23 AE Signals Obtained with Horizontal Placement of the Sensor Filtered Using FFT
Figure 4.24 De-noised Signal Using Wavelet and FFT (Test VN)

Figure 4.25 De-noised Signal Using Wavelet and FFT (Test VS1)

Figure 4.26 De-noised Signal Using Wavelet and FFT (Test VS2)
Figures 4.25 to 4.26 illustrate the de-noised signals obtained with a relatively slow rate of shearing with vertical placement of sensor. Signals de-noised using FFT and wavelet follow the same pattern. In both tests, the maximum positive peak AE value occurs after 60 seconds of the testing period. Also, the maximum peak values are higher than 0.04V.

Figure 4.27 De-noised Signal Using Wavelet and FFT (Test VF1)

Figure 4.28 De-noised Signal Using Wavelet and FFT (Test VF2)

Figures 4.27 to 4.28 illustrate the de-noised signals obtained with a relatively fast rate of shearing with vertical placement of sensor. Signals de-noised using FFT and wavelet follow the same pattern. Also, the maximum peak values are higher than 0.04V.
Figure 4.29 De-noised Signal Using Wavelet and FFT (Test VNS)

Figure 4.29 illustrates the de-noised signals obtained with no shearing with vertical placement of the sensor. In this case, the maximum positive peak value is less than 0.025V. It is observed that there is a significant difference in terms of AE peak value obtained with and without shearing.

Figure 4.30 AE Signals Obtained with Vertical Placement of the Sensor Filtered Using Wavelet
As seen in Figures 4.22 and 4.23 as well as Figures 4.30 and 4.31, the signals filtered using FFT and wavelet follow the same pattern and more or less coincide with each other. In both cases of horizontal and vertical placement of the sensors, however, one can distinguish the difference between the above two analysis when the signal contains rapid changes. One can observe how the FFT smoothens the signals wherever the data contains rapid changes, whereas, the wavelet analysis provides a clearer view of the spikes or rapid changes of AE. Moreover, it is found that wavelet analysis is a less time consuming approach than FFT.

Figure 4.31 AE Signals Obtained with Vertical Placement of the Sensor Filtered Using FFT
Figures 4.32 and 4.33 represent the maximum positive amplitudes and the absolute values of the maximum negative amplitudes obtained during testing with horizontal and vertical placements of the mote-sensor respectively, for different rates of shearing. Furthermore, Figures 4.32 and 4.33 clearly show that the maximum amplitudes of AE signals received are greater than the maximum amplitude that is obtained during the no shear condition. These maximum amplitudes are also higher than 0.1V under shearing in both horizontal and vertical placement of the sensor. In addition, for both the
horizontal and vertical placement of the sensor, the average maximum positive amplitudes obtained during the faster rate of shearing seem to be slightly higher than that of slower rate of shearing (Figure 4.34).

![Figure 4.34 Plot of Average Maximum Amplitude of AE Signal with Slow and Fast Rate of Shearing](image)

**Figure 4.34** Plot of Average Maximum Amplitude of AE Signal with Slow and Fast Rate of Shearing

![Figure 4.35 Plot Of Maximum Positive and Absolute Maximum of Negative Peak Values Obtained From De-noised Signals Using Wavelet and FFT](image)

**Figure 4.35** Plot Of Maximum Positive and Absolute Maximum of Negative Peak Values Obtained From De-noised Signals Using Wavelet and FFT
Figure 4.35 shows the peak values obtained from the de-noised signals using wavelet and FFT. Except in HF1, the peak values obtained from de-noised signals using FFT are smaller than the peak values obtained from de-noised signals using wavelet. Since these peak values depend on the threshold values used in wavelet analysis and the cut-off range (number of zeros introduced) in the FFT analysis, it is difficult to obtain a definitive relation between the peak values. As shown in Figures 4.32, 4.33 and 4.35, the positive peak values obtained from the original signals and the filtered signals using FFT and wavelet are larger for the faster rate of shearing than for the slower rate of shearing.

The time taken for the occurrence of maximum amplitude is obtained from the de-noised signals using FFT and Wavelet. From Figure 4.36, the occurrence of the maximum positive spikes (peak amplitude) in the faster rate of shearing is quicker than in the slower rate of shearing. This trend is observed for both horizontal and vertical placement of the sensors.
From Figure 4.37, it can be concluded that there is no correlation between the initiation of positive and negative initial visible peak AE activities in each test with different rates of shearing. However, the initial AE activities begin sooner in the faster rate of shearing than in the slower rate of shearing. This is observed in both horizontal and vertical placement of the mote-sensor. The AE data obtained from this study shows that there are several visible AE peak values recorded before they reach their maximum AE values. This behavior would lead one to obtain an early warning of the soil movement well in advance of the actual movement.

4.5 Comparison between Data Obtained from Chemical Mechanical Planarization (CMP) and Delamination Processes

Figure 4.38 Sample Plot of AE Signal from Polishing and Delamination Process
By comparing Figures 4.1 and 4.38, one can recognize the AE signal obtained from the shear test to be basically similar to the AE signal obtained during the process of polishing of a computer chip. In both cases, friction is the major cause of acoustic emission. Since the amplitude of the AE signal obtained during the delamination of computer chips is higher than in the polishing process, the signal obtained during the delamination process has sudden peak values. In soils, delamination is analogous to shear failure of soil after the peak shear value is reached. This particular situation can be clearly observed in Figure 4.1.

4.6 Comparison Between the Experimental Plot of Shear Force Versus Time and Plot Obtained Using AE Signals

Figure 4.39 Sample Plots of Shear Force Versus Time and AE Versus Time

From Figure 4.39, one can conclude that the maximum AE activity seems to be happening around the time at which the soil reaches its peak stress. Since shear force versus time and AE versus time data were obtained from completely different tests, it can not be directly correlated. However in both cases, one can observe the time-lag between the peak values.
4.7 Suggestion for Future Work

Following suggestions can be offered for the enhancement of the AE signal obtained from shear tests:

1. Introduce a pre-amplifier:

   The output signal from the acoustic emission sensor is typically of very low magnitude and hence the signal-to-noise ratio (SNR) is relatively small. A pre-amplifier boosts this signal to a higher voltage to enable it to be sent down through the cables without suffering from further attenuation or being significantly affected by the electronic background noise.

2. Introduce a differential sensor with digital oscilloscope which provides two input channels:

   The differential sensor can be used to capture the external noise and eliminate that noise from the signal obtained from AE sources in a real time basis. However, to introduce this sensor, one has to have a data acquisition system with a minimum of two channels.

3. Introduce a band pass filter:

   The band pass filter removes unwanted frequencies and known sources of background noise from known sources. A band pass filter can be selected to complement the sensor in producing a refined signal.

4. Increase the sampling rate:

   Increasing sampling rate provides more details of the captured signal. It helps one to identify the natural frequency of the AE signal. By knowing the frequency of the acoustic emission, one can select suitable sensors and a band pass filter for accurate data acquisition system.

5. Introduce a data acquisition system which can control the triggering value voltage:

   By introducing an appropriate triggering value, one can reduce the number of unwanted data captured by the AE sensors.
CHAPTER 5
CONCLUSIONS

5.1 Conclusions

Acoustic emission activities depend on the release of energy as transient elastic waves emanating from the stressed materials. An experimental study was performed in this research on cohesionless soil to show that the acoustic emission (AE) activities result upon direct shearing of soil. The testing was conducted at two different rates of shearing and with horizontal and vertical orientation of a mote-sensor especially designed to sense AE signals. The original signals were filtered using both Fast Fourier Transform and Wavelet analysis.

According to the data obtained from the AE mote-sensor under direct shear, the number of AE events and their amplitudes increase with time and reach peak values before gradually diminishing towards the end of shearing. The following additional conclusions can be drawn from the test results:

1. Comparison of AE signals obtained from shearing and no shear conditions revealed that a significant amount of AE activity is created for fast shearing rates while the sand was being sheared.

2. Comparison of AE signals obtained from fast rates of shearing and slow rates of shearing conditions revealed that the low frequency acoustic emission activity is only significant under fast rates of shearing and it seems to occur around the time at which the soil mobilizes its peak shear stress.

3. Visible AE activity, which is due to particle relocations, can be observed well before the AE activity produces rapid changes and the maximum peak AE values.
4. The occurrence of the initial visible AE peak values as well as the maximum positive peak amplitude is quicker in fast rates of shearing when compared to that in slow rates of shearing.

5. Comparison of AE signals obtained from the tests performed under different rates of shearing showed that the positive peak values obtained with relatively faster rates of shearing are significantly greater than that obtained with slower rates of shearing, perhaps due to the release of more elastic energy in rapid shearing.

6. The filtered signals were obtained using the FFT and wavelet analysis. The energy lost in both cases is more or less the same. Typically, the results obtained from these two analyses followed the same pattern; however, FFT smoothens the curve wherever rapid changes occur; whereas the wavelet approach retains the observed spikes in the original signal. Especially for large amounts of raw data, wavelet analysis approach is more efficient because it yields more accurate filtered signals and also consumes less time for the filtering process.

7. When AE signals obtained after de-noising and the original signals are considered, it is observed that the peak AE values obtained using FFT is smaller than that obtained from wavelet analysis. Since the peak values depend on the appropriate threshold value selected in wavelet analysis and the cut-off introduced in the FFT, one needs to be aware of the sensitivity of the threshold value used in wavelet analysis and the cut-off in FFT.

8. The discrete wavelet transformation (DWT) algorithm provides a fast and efficient means of analysis. The wavelet decomposition of a time series offers a variety of applications on statistical signal analysis not only on periodical signals where Fourier transformation is typically used but also in the analysis of transient
type signals. It can be concluded that the wavelet transform is a relatively fast, easy and effective tool for filtering and de-noising acoustic emission signals.

5.2 Limitations of the Test

1. As seen in the power spectral density (PSD) obtained with a relatively small sampling rate, the dominant frequency range of the signal is very low (less than 1Hz). However, since the sampling rate used in the experiments was small, it cannot be concluded that the dominant frequency of acoustic emission is less than 1Hz. If one uses a much higher sampling rate, one may perhaps obtain a PSD with another range dominated by higher frequency AE signals.

2. The shear force versus time plots obtained from fast and slow rates of shearing show that there is a significant time-lag between the occurrences of shear failure. Since the shear force versus time and the acoustic emission versus time plots were obtained using completely different tests, the peak AE and peak shear force obtained cannot be correlated. By introducing an experimental setup which includes both a load cell and an AE sensor, one could come up with a correlation between the occurrences of peak AE and shear failure of the soil.

3. From the filtered signals, one can clearly observe the occurrence of peak AE activity. Though the original signals show some initial visible peaks, one cannot clearly identify them from the filtered signals probably due to their high frequency. Thus, the implementation of this AE technique in a real time soil movement monitoring system may be difficult without more extensive laboratory experimentation and data analysis.

5.3 Potential Practical Applications

Detection of Acoustic Emission (AE) signals is potentially useful for real time monitoring of impending landslides where the failure planes are predetermined. Since the
field data is generally contaminated by a large amount of surrounding noise, differential sensors must be introduced in order to eliminate the noise. On the other hand, when an AE monitoring system is implemented in the field; one could expect a large number of AE signals. Therefore, a prior knowledge of the AE frequency at early shearing stages can be used with sophisticated filtering techniques like wavelet analysis in real time de-noising of the recorded signals.

To enhance the effectiveness of the monitoring system, an AE monitoring system can be combined with other traditional monitoring systems which use alternative triggering factors such as moisture content, pore water pressure, suction and soil displacement. Thus an appropriate monitoring system can be designed depending on the geologic conditions of the site.
REFERENCES


“Basic Knowledge about Acoustic Emission Method”

“Acoustic Emission Measurement Technologies”

APPENDICES
Appendix A: Plots of Data with Filtered Signals

Figure A.1 Plot of HF1 with Filtered Signal Using Wavelet
Figure A.2 Plot of HF2 with Filtered Signal Using Wavelet
Appendix A: (Continued)

Figure A.3 Plot of HF3 with Filtered Signal Using Wavelet
Appendix A: (Continued)

Figure A.4 Plot of HS1 with Filtered Signal Using Wavelet
Figure A.5 Plot of HS2 with Filtered Signal Using Wavelet
Appendix A: (Continued)

Figure A.6 Plot of HNS with Filtered Signal Using Wavelet
Figure A.7 Plot of VN with Filtered Signal Using Wavelet
Appendix A: (Continued)

Figure A.8 Plot of VS1 with Filtered Signal Using Wavelet
Figure A.9 Plot of VS2 with Filtered Signal Using Wavelet
Figure A.10 Plot of VF1 with Filtered Signal Using Wavelet
Appendix A: (Continued)

![Plot of VF2 with Filtered Signal Using Wavelet](image)

**Figure A.11 Plot of VF2 with Filtered Signal Using Wavelet**